

Sparse Camera Network for Visual Surveillance – A Comprehensive Survey

Mingli Song, *Member, IEEE*, Dacheng Tao, *Senior Member, IEEE*,
and Stephen J. Maybank, *Fellow, IEEE*

Abstract

Technological advances in sensor manufacture, communication, and computing are stimulating the development of new applications that are transforming traditional vision systems into pervasive intelligent camera networks. The analysis of visual cues in multi-camera networks enables a wide range of applications, from smart home and office automation to large area surveillance and traffic surveillance. While dense camera networks - in which most cameras have large overlapping fields of view - are well studied, we are mainly concerned with sparse camera networks. A sparse camera network undertakes large area surveillance using as few cameras as possible, and most cameras have non-overlapping fields of view with one another. The task is challenging due to the lack of knowledge about the topological structure of the network, variations in the appearance and motion of specific tracking targets in different views, and the difficulties of understanding composite events in the network. In this review paper, we present a comprehensive survey of recent research results to address the problems of intra-camera tracking, topological structure learning, target appearance modeling, and global activity understanding in sparse camera networks. A number of current open research issues are discussed.

Index Terms

Sparse camera network, visual surveillance.

M. Song is with the Department of Electrical Engineering, University of Washington, WA 98195.

D. Tao is with the Center for Quantum Computation and Information Systems, University of Technology, Sydney, Australia.
E-mail: dacheng.tao@gmail.com

S. J. Maybank is with the Department of Computer Science and Information Systems, Birkbeck College, University of London, UK.

I. INTRODUCTION

The terrorist attacks that took place in the US in September 2011 resulted in a review of security measures that saw the use of camera networks for a wide range of surveillance tasks become an important research topic. A wide variety of valuable scientific and engineering applications are developed based on the effective use of multi-camera networks. Under the assumption of a dense camera network with large overlapping fields of view (FOV) between cameras, early researchers used geometrical information to calibrate the cameras and reconstruct the shapes and trajectories of objects in the 3D space [1], [2], [3], [4], [5]. Although dense camera networks have been well studied in recent years, sparse camera networks still present challenging problems given that it is necessary to locate, track and analyze targets in a wide area using as few cameras as possible. The cameras in a sparse camera network do not necessarily have overlapping FOVs. An ideal sparse camera network surveillance system should produce the tracking sequences of independently moving objects, regardless of the number of cameras in the camera network or the extent of the overlap between different FOVs [6].

To successfully carry out automatic video surveillance in a sparse camera network, several challenges must be tackled. The first key challenge is track correspondence modeling to meet the requirement of accurate maintenance of person identity across different cameras. The goal of track correspondence modeling is to estimate which tracks result from the same object even though the tracks are captured by different cameras and at different times. Ideally, by combining the local trajectories of individuals obtained from different cameras, the activities of the individuals can be understood in a global view (Figure 1). The identification of corresponding tracks is made more difficult by the changes in the appearance of an individual from the FOV of one camera view to that of another. Causes of these changes include variations in illumination, pose and camera parameters.

The second key challenge for a sparse camera network-based video surveillance system is how to learn the relationship between the cameras. 'Spatial topology' refers to distribution and linkage and is utilized to predict the trajectories of targets in a sparse camera network. For example, if a target disappears from the FOV of camera 1, then knowledge of the position of all cameras may allow the inference that the exit from camera 1 is linked to the entrance of the target into the FOV of camera 2 and camera 3. This inference may be supported by similarities in

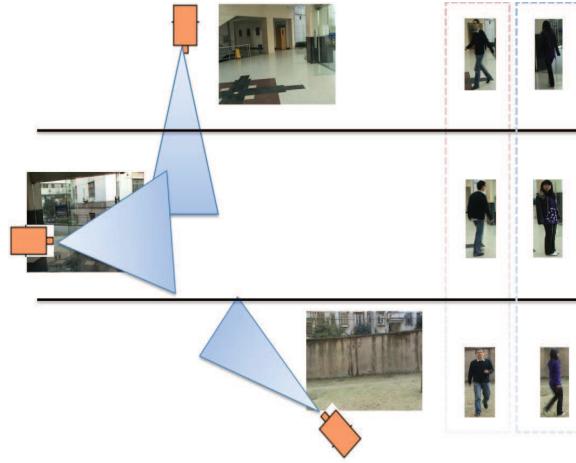


Fig. 1. Tracking targets in a camera network by combining the local trajectories of each individual

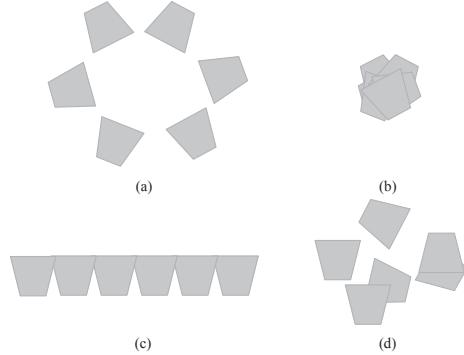


Fig. 2. Different types of overlap (the gray regions indicate the each camera's field of view (FOV). (a) Totally non-overlapping. (b) Totally overlapping. (c) Each camera has an FOV which overlaps with the FOVs of other cameras. (d) A general case that contains each of the overlap types (a)-(c).

the appearance in the different images. Such inferences depend on the topological relationships between the cameras in the network. As shown in Figure 2, these relationships may be of several different types [6]. If the camera network is dense, there are various methods for multi-camera tracking with overlapping FOVs and, as discussed in the literature, there are various geometric matching methods for manually calibrating the cameras [1], [2], [7], [8], [9], [10]. The methods used in these papers can compute the transformation between 2D image coordinates and 3D spatial coordinates for a ground plane. However, it is unrealistic to expect that the FOVs of all the cameras always overlap one another, and the need for all cameras to be calibrated to the

same ground plane usually cannot be satisfied. For instance, a target may appear in the FOV of two different cameras initially and may disappear from one of the FOVs, reappearing after some time in the FOV of a third camera. Several approaches have recently been presented to estimate the spatial topology and linkage in a camera network [11], [12], [13], [14], [15], [16], instead of directly calculating the 3D position in the ground plane, as in [1], [2] and [7], [8], [9], [10].

The third challenge is global activity understanding. For an intelligent video surveillance system, it is not enough to only track the targets without further analysis. Through the global automatic and comprehensive analysis of targets in a sparse camera network, the activities of the targets are understood and anomalous events are detected. Several previous surveys, e.g., [17], have discussed activity understanding. A sparse camera network-based video surveillance system usually covers a much larger area, and hence it usually provides more information about the target's trajectory and activities than a single camera or a conventional dense camera network monitoring a small area. However, because the camera network is sparse, it is necessary to carry out global activity understanding from a new point of view.

Figure 3 shows a flowchart of the data processing steps in a sparse camera network-based video surveillance system. Intra-camera tracking is carried out to identify the target of interest. Subsequently, the appearances, trajectories, and actions of the target in each local camera are measured and analyzed. By labeling the data collected by the sparse camera network to construct a training dataset, we can model the track correspondences of the target and learn the topological relationships between the cameras. Finally, the track correspondences, the topological relationships and the action of the target in each camera are integrated to obtain the global activity understanding.

The rest of the paper is organized as follows. We discuss intra-camera tracking techniques in Section 2. In Section 3, inter-camera track correspondence approaches are reviewed. Section 4 provides a discussion of camera relationships. Global activity understanding is discussed in Section 5. We introduce a number of open issues in sparse camera network-based video surveillance techniques in Section 6. Section 7 summarizes the paper.

II. INTRA-CAMERA TRACKING

A sparse camera network usually monitors a large area, and there are often several targets of interest to be tracked, not only across the whole area but also in the local area covered by a single

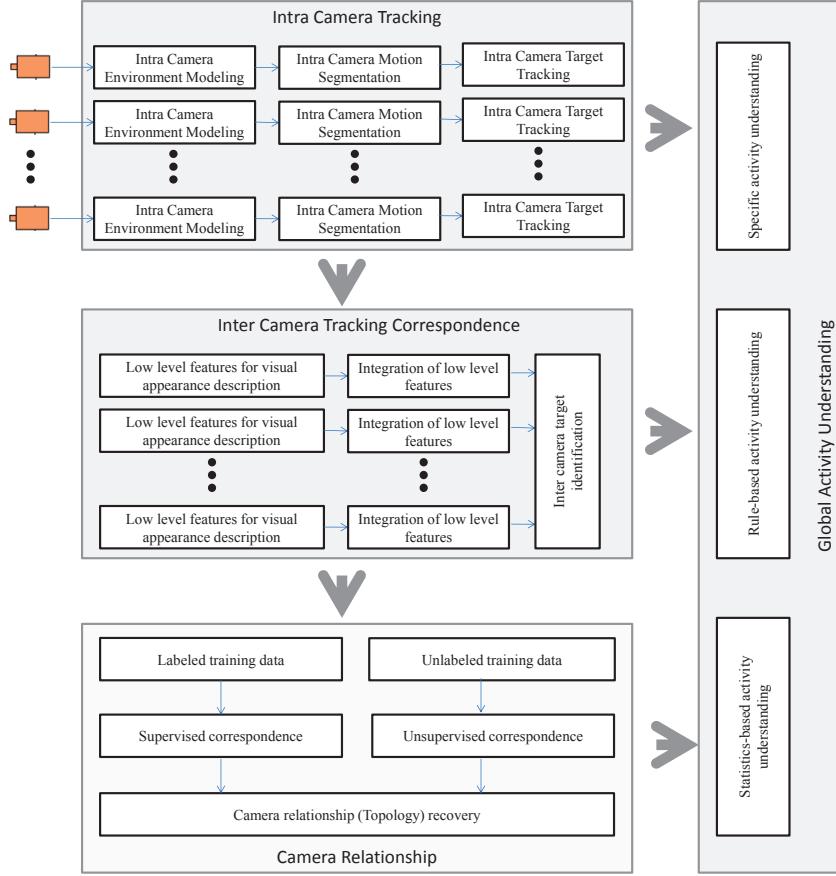


Fig. 3. A flowchart of processing steps for multi-camera network surveillance.

camera. Intra-camera tracking of multiple objects in a single camera is thus the fundamental research problem for sparse camera network-based video surveillance systems. Although there are good algorithms [18], [19] for tracking isolated objects or small numbers of objects undergoing transient occlusions, the intra-camera tracking of multiple objects still remains challenging due to the effects of background clutter, occlusion, changing articulated pose, and so forth. The goal of intra-camera tracking of multiple objects is to extract as much visual information as possible about each target of interest from each camera view. The information usually includes a consistent label along with size, orientation, velocity, appearance, pose, and action. Intra-camera tracking is often the first processing step before higher level behavior analysis.

Most frameworks for intra-camera tracking of multiple targets include the following stages:

- a) Intra-camera background modeling;

- b) Intra-camera motion segmentation;
- c) Intra-camera target tracking.

A. Intra-Camera Background Modeling

The accuracy and reliability of target tracking is increased by modeling the background against which the target moves. Changes in the environment, such as strong winds, or variations in illumination or shadow orientation, cause background changes even for fixed cameras, in spite of the fact that the background does not move. These changes can cause errors in target tracking. Many approaches to automatically describing the background of images taken by fixed cameras have been presented [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33]. In [20] and [21], the temporal average of image sequences is used to estimate the background. Köhle et al. described the background using an adaptive Gaussian distribution [22], in which the Kalman filter was used to take account of the illumination variation of each pixel. In [23] and [24], the background is updated dynamically using a Gaussian mixture model (GMM). Mckenna et al. [33] proposed an adaptive background model with color and gradient information to reduce the influences of shadows and unreliable color cues based on a GMM. GMMs are usually trained by the EM algorithm or its variants, so the real-time and dynamic nature of surveillance applications prohibits direct use of the batch EM. Lee [25] proposed an effective GMM scheme to improve the speed with which changes in the background can be learned without compromising accuracy. Detailed discussions on GMM-based background modeling methods are given in [26].

Although the GMM is the most widely used method for describing a fixed background, it is not sufficient for a rapidly moving background. As a modification of the conventional GMM-based approach, Sheikh and Shah presented a nonparametric kernel density estimator under the Bayesian framework to model a moving background [27]. Monnet et al. [28] presented an on-line auto-regressive model to capture and predict the behavior of moving backgrounds, and Zhong et al. [31] adopted the Kalman filter to model moving textured backgrounds. Similarly, Heikkila and Pietikainen [32] presented a texture-based method for modeling moving backgrounds in video sequences. The values taken by each pixel are modeled as a group of adaptive local binary pattern histograms. Dong et al. [29] applied Markov random fields (MRF) to represent the foreground and the background, and adopted a local online discriminative algorithm to deal with the interaction among neighboring pixels over time subject to illumination changes.

B. Intra-Camera Motion Segmentation

In a camera network, the moving regions are usually treated as an important prior to indicate the position of the tracked target in the cameras' FOV; intra-camera motion segmentation is therefore usually required to detect moving regions. Briefly, the existing approaches for motion segmentation can be divided into two groups: background subtraction and optical flow.

1) Background subtraction: Background subtraction is a classic method for extracting the motion part from a video. As a result of subtraction, each frame is divided into two regions: the foreground that contains the targets of interest and the background without targets of interest. Many background subtraction techniques have been presented in the past decades [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46].

In the influential real time visual surveillance system W⁴ [45], the background is subtracted by taking into account three components: a detection support map, a motion support map and a change history map. The first component records the number of times a pixel is classified as the background in the last N frames, the second component records the number of times a pixel is associated with a non-zero optical flow, and the third component records the time that has elapsed since the pixel is last classified as a foreground pixel. In [34], Seki et al. carried out the background subtraction on the assumption that neighboring blocks of background pixels should follow similar variations over time. Principal Component Analysis (PCA) is used to model the background in each block, but PCA-like approaches usually face a memory problem in storing the series of frames required for PCA. Jodoin et al. [37] consequently proposed using a single background frame to train a statistical model for background subtraction. More robustly, Yao and Odobez [35] presented a multi-layer background subtraction technique which handles the background scene changes that result from the addition or removal of stationary objects by using local texture features represented by local binary patterns and photometric invariant color measurements in the RGB color space. Lin et al. [42] segmented the foreground from the background by learning a classifier based on a two-level mechanism for combining the bottom-up and top-down information. The classifier recognizes the background in real time. Similarly, hierarchical conditional random fields were employed to carry out background/foreground segmentation in [36]. A generic conditional random fields-based classifier was used to determine whether or not an image region contained foreground pixels. The above classifiers are usually not able to deal

successfully with rapidly moving backgrounds; hence, Mahadevan and Vasconcelos [38] proposed a bio-inspired unsupervised algorithm to deal with this problem. Background subtraction is treated as the dual problem of saliency detection: background pixels are those considered not salient by a suitable comparison of target and background appearance and dynamics.

By formulating the background subtraction problem in a graph theoretic framework, Ferrari et al. [39] segmented the foreground from the background by using the normalized cuts criterion. Criminisi et al. [40] enhanced the efficiency and consistency of background subtraction by applying a temporal constraint based on a spatio-temporal Hidden Markov Model (HMM). Similarly, by combining region-based motion segmentation and MRF, Huang et al. [41] formulated the background subtraction as a Maximum a Posteriori (MAP) problem.

Background subtraction can also be treated as a background reconstruction problem. In [44], the background was reconstructed by copying areas from input frames based on the assumption that the background color will remain stationary; the motion boundaries are a subset of intensity edges to resolve ambiguities. The background reconstruction problem can thus be formulated as a standard minimum cost labeling problem, i.e., the label for an output pixel is the frame number from which to copy the background color, and the labeling cost at a pixel will be increased when it violates the above two assumptions. Motivated by the sparse representation concept, background subtraction was recently regarded as a sparse error recovery problem in [43]. The difference between the processed frame and estimated background was measured using an L_1 norm.

2) *Optical flow*: Optical flow is another classic and widely used technique for motion detection. Optical flow-based motion segmentation methods can detect the motion of a foreground target even if the camera is not fixed. For instance, optical flow is used to track and extract articulated objects in [47], [48], [49], [50]. The optical flow can be computed based on the gradient field [51], [52], [53] deduced from the displacement between two frames taken a short time apart. Popular techniques for computing optical flow include methods by Horn and Schunck [54], Lucas and Kanade [55], and others. The conventional techniques for estimating dense optical flow are mainly local, gradient-based matching of pixel gray values combined with a global smoothness assumption. In practice, this assumption is usually untenable because of motion discontinuities and occlusions. These limitations arising from the global smoothness assumption were tackled in [56], [57], [58], [59]. In [56], a robust ρ -function, truncated quadratic is adopted to reduce

the sensitivity to violations of the brightness constancy and spatial smoothness assumptions. To improve the accuracy and robustness of optical flow computation, Lei and Yang [58] presented a coarse-to-fine region tree-based model by treating the input image as a tree of over-segmented regions; the optical flow is estimated based on this region-tree using dynamic programming. To accommodate the sampling-inefficiency problem in the solution process, the coarse-to-fine strategy is applied to both spatial and solution domains.

Paperberg et al. [57] presented a variational model for optical flow computation by assuming grey value, gradient, Laplacian and Hessian constancies along trajectories. Since the model does not linearize these constancy assumptions, it is able to handle large displacements. This variational model exploits the coarse-to-fine warping method to implement a numerical scheme which minimizes the energy function by conducting two nested fixed point iterations. However, this coarse-to-fine scheme may not perform well in practice when the optical flow is complicated; for example, when it arises from articulated motion or human motion. In [59], a dynamic MRF-based model was employed to carry out optical flow estimation, whereby the optical flow can be estimated through graph-based matching. More recently, Brox and Malik [60] considered the failure of contemporary optical flow methods to reliably capture large displacements as the most limiting factor when applying optical flow. They presented a variational model and a corresponding numerical scheme that deals far more reliably with large displacements by matching rich local image descriptors such as SIFT or HOG.

Unfortunately, optical flow-based methods have a high time complexity and a low tolerance to noise [61]. In practice, it is difficult to implement optical flow-based methods for real time applications. To strengthen the computational efficiency of optical flow, Díaz et al. [62] presented a super-pipelined high-performance optical-flow computation architecture, which achieves 170 frames per second at a resolution of 800×600 pixels.

C. Intra-Camera Target Tracking

Intra-camera target tracking involves two tasks: 1) producing the regions of interest (ROI, bounding box or ellipse) around the targets in each frame, and 2) matching the ROI from one frame to the next. Surveys conducted in [50] and [63] provide sound discussion on existing intra-camera tracking technologies.

To deal with the first task, color, shape, texture or parts of the foreground are usually used to

match with a pre-trained target appearance model and predict whether a target is present [64]. Target detection can be performed by learning different object appearances automatically from a set of examples by means of a supervised learning algorithm. Given a set of learning examples, supervised learning methods generate a function that maps inputs to desired classification results; thus, locating the target in the current frame is a typical classification problem in which the classifier generates a class label. The visual features play an important role in the classification, hence it is important to use features which are capable of identifying one target by classifying the region in a ROI into ‘target’ or ‘background’. To benefit from the visual features, a series of different learning approaches have been presented to separate one target from another in a high dimensional feature space. As the visual features and the classifiers can also be used in intra-camera target detection, we will discuss them in Section 3.

For the second task, the aim of matching ROIs is to generate the trajectory of a target over time in a sequence of frames taken by a single camera. The tasks of detecting the target and establishing correspondences between the ROIs can be carried out separately or jointly. In the separate case, the target is detected in each frame using the methods described above, and we do not therefore consider this case further. In the joint case, the target and the correspondences are jointly estimated by iteratively updating the target location and the size of ROI obtained from previous frames. Visual features from consecutive frames are extracted to match for ROI association in these frames. Many methods for matching ROIs are described in the literature [50]. These methods can be divided into point tracking, kernel tracking and silhouette tracking.

In point tracking, targets in consecutive frames are represented by points in an ROI and the association of the target is based on the previous state of the points in the ROI which reflects the target position and motion. This method requires an external mechanism to detect the targets by an ROI in every frame.

In kernel tracking, the shape and appearance of the target are represented by spatial masking with isotropic kernels so that the target can be tracked by computing the motion of the kernel in consecutive frames. The kernels are usually rectangular templates [65] or elliptical shapes [66] with corresponding histograms.

In silhouette tracking, contour representation defines the boundary of a target. The region inside the contour is called the silhouette of the target. Silhouette and contour representations are suitable for tracking complex non-rigid shapes. Silhouette tracking is carried out by estimating

the target region in each frame. Silhouette tracking methods use the information encoded inside the target region, and this information is modeled as appearance density and shape models, which are usually in the form of edge maps. The silhouettes are generally tracked by either shape matching or contour evolution, which can be treated as target segmentation using the tracking result generated from the previous frames.

Yilmaz and Javed [50], and Velastin and Xu [63] have given good reviews of the above-mentioned tracking methods.

Background subtraction is followed by blob detection in [67]. The blobs are classified into different target categories. A hierarchical modification is developed for hand tracking [68]. In [69], pixels are encoded by HMM, and matched with pre-trained hierarchical models of humans. In [70], [71], [72], both foreground blobs and color histogram are employed to model people in image sequences, and a particle filter is used to predict their trajectories. The states of multiple interacting targets in such particle filters are estimated using MCMC samplings based on the learned targets' prior interactions.

By casting tracking as a sparse approximation problem, Mei and Ling [73], [74] dealt with occlusion and noise challenges by a series of trivial templates. In their approach, to find the target in a given frame, each target has a sparse representation in a space spanned by target templates and trivial templates, in which the trivial template's unit vector has only one nonzero element. This sparsity is obtained by solving an l_1 -regularized least-squares problem, and the candidate with the smallest projection error is treated as the tracking target. To enhance computing efficiency, several modified sparse representation-based trackers are further developed by Mei et al. [75], Li [76] and by Liu et al. [77].

To deal with effects such as changes in appearance, varying lighting conditions, cluttered backgrounds, and frame-cuts, Dinh et al. [78] presented a context tracker to exploit the context on-the-fly by maintaining the consistency of a target's appearance and the co-occurrence of local key points around the target. Kwon and Lee [79] proposed a novel tracking framework called a visual tracker sampler. An appropriate tracker is chosen in each frame. The trackers are adapted or newly constructed, depending on the current situation in each frame. Li et al. [80] presented an incremental self-tuning particle filtering framework based on learning an adaptive appearance subspace obtained from SIFT and IPCA. The matching from one framework to the next is classified using an element of the affine group. Similarly, Bolme et al. [81] presented a

new type of correlation filter called a Minimum Output Sum of Squared Error filter to produce stable correlation filters to adapt to changes in the appearance of the target. Ross et al. [82] presented an incremental learning method to obtain a low-dimensional subspace representation of the target and efficiently adapt online to changes in the appearance of the target.

In recent years, tracking by detection has become an important topic. In [83], [64], [84], [85], [86], for instance, the intra-camera tracking of people is carried out by first detecting people in each frame without motion segmentation. The positions of the people in different frames are combined to form a trajectory for each person.

III. INTER-CAMERA TRACKING CORRESPONDENCE

For a sparse camera network, the relationship between cameras, e.g., the topology and the transition times between cameras, is learned based on inter-camera identification. In the scenario of sparse camera network-based visual surveillance, it is thus desirable to determine whether a target of interest in one camera has already been observed elsewhere in the network. This problem can easily be solved for a conventional dense camera network by simply matching the 3D position of the target to the position of each candidate, because the cameras in the network are well calibrated. However, a sparse camera network-based visual surveillance system usually contains a number of cameras without overlapping views because the requirement to maintain calibration is impractical. The basic idea of most existing approaches for non-overlapping camera configurations is to formulate inter-camera target matching as a recognition problem, i.e., the target of interest is described by visual appearance cues and compared with the candidates in videos captured by other cameras in the sparse network. This kind of recognition problem is commonly known as “object identification”, “object re-identification” or “appearance modeling”. When modeling the appearance of a human target in a sparse camera network, a common assumption is that the individual’s clothes stay the same across cameras. However, even accepting this assumption, the intra-camera tracking task remains challenging due to variations in illumination, pose and camera parameters over different cameras in the network.

A generic intra-camera tracking framework can be decomposed into three layers:

- a) Low level features for visual appearance description: extraction of concise features.
- b) Integration of low-level features.
- c) Inter-camera target identification.

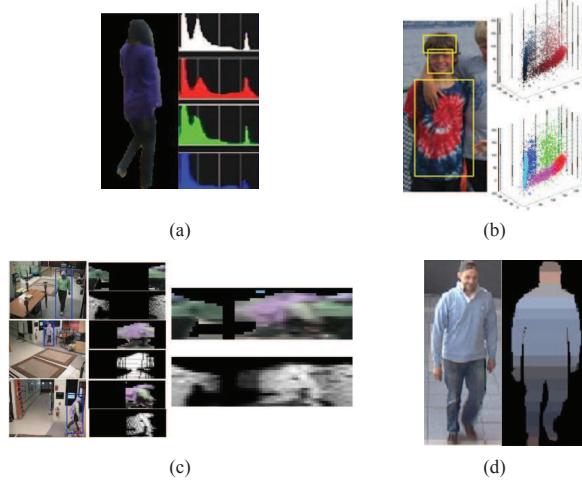


Fig. 4. Examples of global representation features, i.e., (a) global histogram of RGB color [88], (b) GMM [90], (c) panoramic appearance map [92], and (d) color position [93].

A. Low Level Features for Visual Appearance Description

The low level features for visual appearance description can be divided into two categories: global visual features and local visual features. The global visual features encode the target as a whole. The local visual features describe the target as a collection of independent local descriptors, e.g., local patches and Gabor wavelets. A global feature usually contains comprehensive and rich information, so it is very powerful if it is accurate. On the other hand, it is very sensitive to noise, partial occlusions, viewpoint changes and illumination changes. In contrast with global features, local features are less sensitive to these factors; however, as the features are extracted locally, some information, especially spatial information, may be lost.

1) Global visual features: A global feature encodes the tracking target using a single multi-dimensional descriptor. For instance, Huang et al. [87] used the size, velocity and mean value of each channel in HSV color space to describe the appearance of vehicles. In many applications, the target is more complex than a vehicle, and thus stronger descriptors are needed. General global features used to represent a target's appearance include the global histogram [88], [89], GMM [90], [91] and newly defined global descriptors for human re-identification, e.g., panoramic appearance map (PAM) [92] and color position [93].

a) Global histogram:

Histogram-based methods can represent large amounts of information. They are efficient, easy

to implement, and have a relatively high tolerance to noise.

One of the earliest attempts to represent targets by histograms was carried out by Kettnaker and Zabih [94]. In [94], the collection of image sub-regions corresponding to the tracking target is mapped into a coarse partition of the HSV color space. The color space is empirically designed to distinguish between popular clothing colors such as beige, offwhite, or denim, while being coarse enough to achieve robustness to lighting changes. The counts in each color bin across a partition are modeled as Poisson distributed variables. Orefej et al. [95] also extracted histograms of HSV color values of pixels in the target area. PCA is applied to 6,000 histograms of HSV color values and HOG descriptors, and the eigenvectors corresponding to the top 30 eigenvalues are extracted as the final representation. Morioka et al. [96] calculated the covariance matrix of color histograms and projected the set of color histograms onto the eigenspace spanned by the eigenvectors corresponding to the first d largest eigenvalues. Porikli [97] used a brightness transfer function (BTF) between every pair of cameras to map an observed color value in one camera to the corresponding observed color value in the other camera. Once this mapping is known, the inter-camera correspondence problem is reduced to the matching of transformed histograms of color. Lin and Davis [98] proposed a normalized rgs^1 color to deal with illumination changes since the independence of chromaticity from brightness in this color space allows using a multivariate Gaussian density function to cope with the differences in brightness. Color rank features in [67] encode the relative rank of intensities of each RGB color channel for all sample pixels where the ranked color features are invariant to monotonic color transforms and are very stable under a wide range of illumination changes. Nakajima et al. [88] described a system that learns from examples to recognize persons in images taken indoors. Images of full-body persons are represented by the RGB color histograms (Figure 4(a)), the normalized color histograms and the shape histograms.

b) GMM: Gaussian Mixture Model:

GMM is a parametric probability density function expressed as a weighted sum of Gaussian component densities. A complete GMM is specified by the mean vectors, the covariance matrices and the mixture weights for all the component densities. As any continuous distribution can be approximated arbitrarily by a finite mixture of Gaussian densities with common variance, the

¹ $r = \frac{R}{R+G+B}$ and $g = \frac{G}{R+G+B}$ are two chromacity variables and $s = \frac{R+G+B}{3}$ is a brightness variable.

mixture model can provide a convenient parametric framework to model an unknown distribution. Sivic et al. [90] modeled the parts of human body using a GMM with 5 components in the RGB color space (Figure 4(d)). They argue that the use of a mixture model is important because it can capture the multiple colors of a person’s clothing. The GMM is also widely used to model the distribution of face shape [99], [100], [101], and has application in human identification.

c) Newly defined global descriptors for human re-identification:

Gandhi et al. [92] developed the concept of a PAM (Figure 4(b)) for performing person re-identification in a multi-camera setup. A PAM centering on the person’s location is created with the horizontal axis representing the azimuth angle and the vertical axis representing the height. PAM models the appearance of a person’s body as a convex generalized cylinder. Each point in the map is parameterized by the azimuth angle and height, and the radius of the cylinder is treated as constant. This allows PAM extracts and combines information from all the cameras that view the object features to form a single signature. The horizontal axis of the map represents the azimuth angle with respect to the world coordinate system, and the vertical axis represents the object height above the ground plane. Cong et al. [93] proposed a color-position histogram (Figure 4(c)), in which the silhouette of the target is vertically divided into equal bins and the mean color of each bin is computed to characterize that bin. Compared to the classical color histogram, it consists of spatial information and uses less memory. Moreover, this new feature is a simpler and more reliable measurement for comparing two silhouettes for person re-identification.

2) Local visual features:

a) Local visual feature detection:

Examples of local visual features include corners, contour intersections and pixels with unusually high or low gray levels. Contour intersections often take the form of bi-directional signal changes and the points detected at different scales do not move along a straight bisector line; hence, corners are often detected using local high curvature maxima [102]. Unlike high curvature detection, local visual feature detection based on image intensity makes few assumptions about the local gray level structure and is applicable to a wide range of images. A second-order Taylor expansion of the intensity surface yields the Hessian matrix [103] of second order derivations. The determinant of this matrix reaches a maximum for blob-like structures in the image; thus the interest points can be localized when the maximal and minimal eigen-values of the second

moment matrix become equal. In the gradient-based approach, local features are detected using first-order derivatives. The gradient-based local feature detector returns points at the local maxima of a directional variance measure. A typical and well known gradient-based local feature detector is the Harris-Stephens detector [104], which is based on the auto-correlation matrix for describing the gradient distribution in the local neighborhood of a point. Lowe [105] proposed localizing points at local scale-space maxima of the difference of Gaussians. Dollár [106] applied Gabor filters separately in the spatial and temporal domains. By changing the spatial and temporal size of the neighborhood in which local minima are selected, the number of interest points can be adjusted. Laptev [107] extended the Harris-Stephens corner detector to space-time interest points where the local neighborhood has significant variation in both the spatial and the temporal domains.

b) Local visual feature descriptor:

An image can be described using a collection of local descriptors or patches that can be sampled densely or at points of interest. Compared to extracting local descriptors at the interest point, dense sampling retains more information, but at a higher computational cost. A performance evaluation of different local visual feature descriptors has been given by Mikolajczyk and Schmid [108]. We discuss the different types of descriptors as follows.

(1) Distribution descriptors

Distributions of intensity [109], gradient [105], [110] and shape [111] are widely used as local descriptors. Zheng et al. [112] extracted SIFT features [105] (Figure 5 (b)) for each RGB channel at each pixel to associate a group of people over space and time in different cameras. These features are clustered and quantized by K-means to build a codebook. The original image is then transformed to a labeled image by assigning a visual word index to the corresponding feature at each pixel of the original image. Wang et al. [113] extracted Histogram of Gradients (HOG) [110] features in the Log-RGB space. They argued that taking the gradient of the Log-RGB space had an effect similar to homomorphic filtering, and made the descriptor robust to illumination changes. Hamdoun et al. [114] utilized a method in [109] known as SURF to detect interest points; it was Hessian-based and used an integral image for efficient computation. The descriptors SURF are 64 dimension vectors which coarsely describe the distribution of Haar-wavelet responses in sub-regions around the corresponding pixels of interest. Laptev and Lindeberg [115] presented a local spatio-temporal descriptor that included position dependent

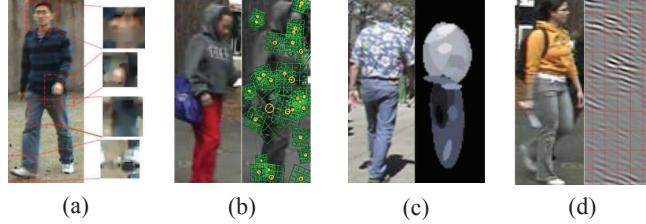


Fig. 5. Examples of local visual features, i.e. (a) local epitome [120], (b) SIFT [112], (c) MSCR [122], and (d) local Gabor filter [117].

histograms and the PCA-based dimensionality reduced spatial-temporal gradients around the spatio-temporal interest points.

(2) Frequency descriptors

The spatial frequencies of an image carry important texture information and can be obtained by the Fourier transform and the wavelet transforms, such as Haar transform and Gabor transform. In contrast to the Fourier transform and the Haar transform, in which the basis functions are infinite, the Gabor transform [116] uses an exponential weighting function to localize the decomposition of an image region into a sum of basis functions. The region to analyze is first smoothed using a Gaussian filter, and the resulting region is then transformed with a Fourier transform to obtain the time-frequency analysis. Gray et al. [117] used two families of texture filters, taken from Schmid [118] and Gabor [119] respectively, on eight color channels corresponding to the three separate channels of the RGB, YCbCr, and HSV color space, in which the used eight color channels contain only one of the luminance (Y and V) channels.

(3) Other local descriptors

Bazznai et al. [120] utilized local epitome [121] to focus on regions (Figure 5 (a)) that contain highly informative repeating patches. Farenzena et al. [122] used a Maximally Stable Color Regions (MSCR) operator [123] (Figure 5 (c)) to detect blobs which constitute the maximally stable color regions over a range of frames. The detected blob regions are described by their area, centroid, second moment matrix and average color.

B. Integration of Low-Level Features

Methods for integrating low-level features can be grouped into three classes: the template-based approach, biometric-based approach, and segmentation-based approach. Template-based

approaches typically match low level features to a stored template, whereas biometric-based approaches use biometrics such as gait, face or gesture to organize low-level features. Finally, segmentation-based approaches first segment the image into small sub-regions, and then register them so that the corresponding sub-regions can be integrated. Note that the divisions between the three classes are not strict, and some methods may be grouped into two or three classes.

1) Template-based approach: Santner et al.[86] employed a rectangular template for the static description of objects and used the mean shift algorithm to track objects. Bird et al. [123] used a strip-based rigid template to organize the low level features of the target's appearance by dividing the image of a pedestrian into ten equally spaced horizontal strips. The mean feature vectors of the horizontal strips are learned in the training step and are used as the template parameters of each pedestrian class. Zheng et al. [112] defined a holistic rectangular ring structure template to organize low level features to model the appearance of a group of people. They argued that the rectangular ring structure was robust to the changes in the relative positions of the members in the group.

2) Biometric-based approaches: Thome et al. [124] organized the low level features from a 2-D body image to represent the human shape, i.e., the human shape is divided into six parts: head, torso, two legs, and two arms, each of which is represented by a rectangle. This method works well if all the parts can be properly recognized. Sivic et al. [90] described a person using a pictorial structure with three rectangular parts corresponding to the hair, face and torso. Each part is modeled by a GMM for pixel values. A similar approach is proposed by Song et al. [125], who first extracted the low level features, e.g., color, texture, shape, etc., and then represented the biometric properties by the visual word learned from the color distribution. Tao et al. [126] developed general tensor discriminant analysis to model Gabor gait for recognition. Seigneur et al. [127] applied region-merging via a boundary-melting algorithm [128] to segment a blob into distinct features for recognition, including skin, face, hair, and height. Wang et al. [129] used the dynamics of walking motion to represent the gait of a person, and the distance between the outer contour and the centroid of a body silhouette was calculated to construct a gait pattern, which was processed by PCA to reduce the dimension of the gait patterns.

3) Segmentation-based approach: Gheissari et al. [130] proposed a spatio-temporal over-segmentation method that groups pixels belonging to the same type of fabric according to their low level features (e.g., color). Two groups are merged when the distance between them is less

than the internal variation of each individual group. Oreifej et al. [95] segmented foreground blobs in aerial images by using low dimensional features, such as color, texture, etc., following which every blob region was assigned a weight. The most consistent regions were given a higher weight to enable the identification of the target in different observations, because they were more likely to lead to the target's identity.

C. Inter-Camera Target Identification

Inter-camera target identification is usually treated as a conventional classification problem, in which the same target is tracked from different views in the sparse camera network. Once the visual appearance of the target has been described using the low level features, a series of classification methods can be employed to identify the target in the different views. These classification methods are as follows.

1) Nearest neighbor: A significant number of methods [95], [112], [120], [121], [130], use single k-nearest neighbor (KNN) classifier to identify a target. The similarity between the appearance of the observed target and that of the targets in a training set is measured using a chosen distance, e.g., Euclidean distance, geodesic distance, etc. In [95], candidate blobs are represented as nodes in a PageRank Graph [131] to extract distinguishing regions. By representing each region as a feature vector (a distribution in the feature space), the blob is described by a collection of distributions. In [132], the KNN-based target identification is based on the Earth Mover Distance between two blobs which is computed as the minimum cost of matching multiple regions from the first blob to multiple regions from the second. In [112], two local descriptors, SIFT+RGB and Center Rectangle Ring Ratio-Occurrence are used to represent the appearance of human, and a distance metric is defined using these two descriptors in a regularized form. A nearest neighbor-based matching approach is adopted to associate targets from different cameras. In [120], a new matching distance between candidate targets from different cameras is defined using the Histogram Plus Epitome (HPE), in which both local and global low level features are organized. Targets are matched between views using the minimum matching distance. Similar to [120], a new matching distance is defined in [121] by taking into account both the local and the global low level features. As in [120], targets are matched between views using the minimum matching distance. In [130], a template-based matching strategy is used to match targets between views.

2) Generative model for target identification: In [90], pictorial structures are used to detect people, and the distance between the pictorial structures from different people is computed based on the image appearance likelihood and the prior probability of the spatial configuration. The most probable desired target can be found using an MAP framework to integrate the image appearance likelihood and the prior probability of the spatial configuration, based on the Bayesian theorem. In a more general way, codebook can be used to integrate color, shape and texture. Using the codebook, generative approaches can model the visual appearance in terms of conditional density distribution over the candidate targets. A graphical model using a Bayesian formula is constructed in [11] to describe the joint distribution of the target's transition from camera to camera. The joint distribution is computed over all probabilities, including the prior of the appearance of the detected target, the distribution of the appearance, the transition probability between cameras, the distribution of transition times between cameras, the intra-camera typical path distribution and the camera distribution where an object may enter the camera network. The posterior probability for the identity of a target can be inferred by combining these priors and conditional distributions. By using the Bayesian formula, the posterior probability for the identity of a vehicle is inferred in [87] by combining the appearance prior and location conditional distributions.

3) Discriminative model for target identification: Discriminative classifiers predict the class label directly without a full model for each class. Examples of discriminative classifiers include Support Vector Machine (SVM) [133], Adaboost [117], Cascade [134], and SNoW [135]. In [117], an Adaboost algorithm is employed to select local features which include the target template and the color histogram for the target appearance. Based on the selected local features, a similarity function is learned for target identification across different views. In [134], a cascade target detection approach based on the deformable part models [136] is proposed. The target is represented by a grammatical model for the parts of the target. In [135], a sparse, part-based representation of the target is constructed and a Sparse Network of Windows (SNoW)-based learning architecture is employed to learn a linear classifier over the sparse target representation. Inspired by the part-based detection approaches, Dollr et al. [137] presented a multiple component learning method for target detection. The method automatically learns individual component classifiers and combines these into an integrated classifier. In [133], a set of features based on color, textures and edges is used to describe the appearance of the target. By using Partial Least

Squares, the features are weighted according to their discriminative power for each different appearance. The weights are helpful for improving the discriminative ability of Support Vector Machine (SVM) to identify the target in different views. Similarly in [17], sparse Bayesian regression is employed to train an SVM for efficient face tracking between frames, and in [138], an SVM is trained for multiple part-based target detection and tracking under occlusion. Recently, a discriminatively trained part-based model [139] was presented for target detection in different views, in which a latent SVM is proposed by reformulating Multi-Instance SVM [140].

IV. CAMERA RELATIONSHIP

Difficult scenarios may arise when multiple targets with similar appearances are simultaneously present in a sparse camera network. The relationships between the cameras can help to identify targets across views when the visual appearance alone is insufficient.

The type of camera relationship in a sparse camera network differs from the conventional dense camera network because it is not assumed that there are overlapping views. For sparse camera networks with non-overlapping views, or a combination of non-overlapping FOVs and overlapping FOVs, the relationship between cameras, e.g., the topology and transition times between cameras, is learned from inter-camera identification, as discussed in Section III.

Obtaining the relationship across cameras with non-overlapping FOVs is a challenging problem. It is preferable if the tracking system does not require camera calibration or complete site modeling, since either it is expensive to fully calibrate cameras or site models are unavailable in a sparse camera network.

The space-time topology of a sparse camera network is represented by a graph which describes the observed behavior of targets in the network. The nodes represent view units, such as cameras or entry/exit zones, and the edges describe the paths that targets can take between the nodes. The edges may be weighted to describe the probability that a target will move from one node to another. An additional distribution over time may be added to each edge to describe the movement between nodes.

A. Camera Relationship Recovery based on Supervised Correspondence

A large number of works have addressed the problem of camera relationship recovery across non-overlapping FOVs. Some rely on manually labeled target correspondences or the assumption

of an accurate appearance model [11], [16], [141], [142], [143], [144], [145]. The basic assumption of such approaches is intuitive: if there is a trajectory which is viewed by two cameras in the network, possibly at different times, then the two cameras should be linked. Javed et al. in [16], [141], [145] used labeled data to train a BTF (see Section III-A1) between each pair of cameras to estimate target correspondences, and then used a non-parametric method, Parzen windows, to learn the links between pairs of nodes. Chen et al. [142] also used BTF to estimate target correspondences. They manually labeled pairs of adjacent cameras and closed blind regions as prior knowledge. The entry/exit zone-based spatio-temporal relationships, entry/exit zones and transition probability between different zones, are thus learned according to the prior knowledge of the camera network topology. Finally, through an MCMC sampling strategy, they can learn the parameters of BTF by adapting to the change in the topology of cameras.

Farrell et al. [11] presented a Bayesian framework for learning higher order transition models in sparse camera networks. Different from the first-order "adjacency", such higher order transition models reflect both the relationship between cameras in the network, and the object movement tendencies between cameras in the network. To learn the higher-order transition models, a Bayesian framework is used to describe the trajectory association between different cameras. In the Bayesian framework, the high-order transition model parameters can be learned based on the gathered trajectories of targets in the camera network by finding the largest association likelihood. Sheikh and Shah [13] exploited geometric constraints on the relationship between the motions of each target across airborne cameras. Since multiple cameras exist, ensuring coherency in association is an essential requirement; for example, that transitive closure is maintained between more than two cameras. To ensure coherency, the likelihood of different association assignments is computed by a k-dimensional matching process. By using the most likelihood association assignment, canonical trajectories of each target and the optimal assignment of association between cameras in the network are computed by maximizing the likelihood.

Zou et al. [143] integrated face matching in the statistical model to better estimate the correspondence in a time-varying network. A weighted directed graph is built based on the entry/exit nodes to describe the connectivity and transition time distributions of the camera network. By using the face matching results, the statistical dependency between the entry and exit nodes in the camera network can be learned more efficiently. In [14], the inter-camera association is learned using an online discriminative appearance affinity model. This approach

benefits from multiple instances learning to combine three complementary image descriptors and their corresponding similarity measurements. Based on the spatial-temporal information and the defined appearance affinity model, an inter-camera track association framework is presented to solve the “target handover” problem across cameras in the network.

B. Camera Relationship Recovery based on Unsupervised Correspondence

Supervised correspondence methods are often difficult to implement in real situations, especially when the environment changes significantly. Makris et al. [15] proposed a method which does not rely on manually labeled data for learning inter-camera correspondence. When the two cameras in the network track the same target, the network topology is recovered by estimating the transition delay between two cameras, using cross-correlation on unsupervised departure and arrival observations if the target has disappeared from their view. The entry/exit zones of each camera view are initially learned automatically from an extended dataset of observed trajectories, using Expectation Maximization. The entry/exit zones are represented collectively by a GMM, and the links between the entry/exit zones across cameras can then be found using the co-occurrence of entry and exit events. The basic assumption in [15] is that if the correlation between an entry and exit at a certain time interval is much more likely than a random chance, the two nodes have a higher probability of being linked. However, Stauffer et al. [146] argued that the assumptions of a stationary stochastic process of the target leaving and entering scenes and the joint stationary stochastic process of pairs of observations are not suitable, because relative common features in most traffic scenarios do not support this assumption. For instance, traffic events such as stop signs or traffic lights will lead to correlations in interval time across unlinked nodes. Hence, in contrast to [15], their solution is to use a likelihood ratio hypothesis test to determine the presence of the link and the likelihood ratio of transitions. This method can handle cases where exit-entrance events may be correlated but the correlation is not due to valid target exits and entrances.

Gilbert et al. [147] extended Makris’s approach [15] by incorporating coarse-to-fine topology estimations. The coarse topology is obtained by linking all cameras to others. Then, by eliminating the invalid linkages between cameras because they correspond to impossible routes, the topology is refined over time to improve accuracy as more data becomes available. In this approach, color cues are used to help build the linkage despite the fact that this is appearance

information. In contrast to [147], Tieu et al. [148] improved Makris's work [15] in two ways. First, instead of directly learning the correlation between the cameras in a camera network, mutual information (MI) is used to measure the statistical dependence between two cameras. Compared to correlation, MI is more flexible and can explicitly handle target correspondence in different cameras. Second, approximate inference of correspondence using MCMC is performed, which requires samples from the learned posterior distribution of correspondence described by MI without being based on target appearance modeling. Marinakis et al. [149] proposed a method similar to Tieu's work [148] in which they used Monte Carlo Expectation Maximization (MCEM) to estimate the linkage between nodes.

Recently, Loy et al. [150] proposed a framework for modeling correlations between activities in a busy public space surveyed by multiple non-overlapping and uncalibrated cameras. Their approach differs from previous work in that it does not rely on intra-camera tracking. The view of each camera is subdivided into small blocks, and these blocks are grouped into semantic regions according to the similarity of local spatial-temporal patterns. A Cross Canonical Correlation Analysis (xCCA) is formulated to quantify temporal and causal relationships between the regional activities within and across camera views. By mapping the tracking problem to a tree structure, Picus et al. [12] used an optimization criterion based on geometric cues to define the consistency of geometrical and kinematic properties over entire trajectories. An interesting approach developed by Wang et al. [151] is correspondence-free scene modeling in sparse camera networks. In [151], the inter-camera relationship is inferred from trajectories learned under a probabilistic model, in which the trajectories belonging to the same activity, as viewed by different cameras, are grouped into one cluster without the need to find corresponding points on trajectories.

V. GLOBAL ACTIVITY UNDERSTANDING

A sparse camera network-based video surveillance system differs from conventional single camera-based activity understanding [152], [153], [154] because it collects information from many different cameras. The automated global understanding of human activity attracts significant attention due to its great potential in applications, from simple tasks such as tracking and scene modeling to complex tasks such as composite event detection and anomalous activity detection. In this section, we discuss the global activity understanding in three aspects: specific activity understanding for sparse camera networks, rule-based activity understanding and

statistics-based activity understanding.

A. Specific Activity Understanding

Specific activity understanding involves the detection or recognition of specific events which are not complicated and need not be pre-defined. Stringa and Regazzoni [155] presented a surveillance system for the detection of object abandonment. This system provides the human operator with an alarm signal, and information about a 3D position whenever an object is abandoned.

Watanabe et al. [156] built an event detection surveillance system using omnidirectional cameras (ODC). The system identifies moving regions using background and frame subtraction. The moving regions detected in each view are grouped together, and the groups are classified as human, object or unusual noise regions. Finally, the system outputs events in which a person enters or leaves a room, or an object appears or disappears.

Ahmedali and Clark presented a collaborative multi-camera surveillance system [157] to track human targets. In this system, a person detection classifier is trained for each camera using the Winnow algorithm for unsupervised, online learning. Detection performance is improved if there are many cameras with overlapping FOVs.

Kim and Davis in [158] proposed a framework to segment and track people on a ground plane. The centers of all vertical axes of the person across views are mapped to the top view plane and their intersection point on the ground is estimated and used to precisely locate each person on the ground plane.

Prest et al. [159] presented a weakly supervised learning method to recognize the interactions between humans and objects. In this approach, a human is first localized in the image and the relevant object for the action is determined. The recognition model is learned from a set of still images annotated with the action label. After human detection, the spatial relation between the human and the object is determined based on which specific actions are recognized. These actions include playing the trumpet, riding a bike, wearing a hat, cricket batting, cricket bowling, playing croquet, tennis forehand, tennis serve, or using a computer. Wang et al. [160] presented an action recognition method based on dense trajectories in which different actions correspond to different trajectories. Dense points from each frame are tracked, based on a dense optical flow field. The resulting trajectories are robust to fast irregular motions as well as to short time

boundaries. The dense trajectories provide a good summary of the motion in the video. The motion trajectories are encoded by a motion boundary histogram-based descriptor, and specific actions, such as biking, shooting, spiking, kicking, and so forth are recognized.

B. Rule-based Activity Understanding

Compared to specific activity understanding, rule-based activity understanding is more complex and can provide richer information. Allen and Ferguson in [161] defined the rules of actions and events in a framework of interval temporal logic. Similarly, Foresti et al. [162] treated the video-event as a temporal subpart of the predefined temporal logic of events in the framework. Based on Allen and Ferguson's work, Nevatia et al. [163], [164] used ontology to represent complex spatial-temporal events. The ontology consists of a specific vocabulary for describing a certain reality and a set of explicit assumptions regarding the vocabulary's intended meaning. Hence it allows the natural representation of complex events as composites of simpler events. In this ontology-based event recognition system, primitive events are defined directly from the properties of the mobile object. Single-thread composite events are defined as a number of primitive events with temporal sequencing, forming an event thread. Multi-thread composite events are defined as a number of single-thread events with temporal/spatial/logical relationships, possibly involving multiple actors. Two formal languages are developed: VERL [165] to describe the ontology of events, and VEML [166] to annotate instances of the events described in VERL.

Borg et al. [167] presented a visual surveillance system for scene understanding on airport aprons using a bottom-up methodology to infer the video event. There are four types of video events in their system: primitive states, composite states, primitive events and composite events. A primitive state corresponds to a visual property directly computed by a scene tracking module. A composite state corresponds to a combination of primitive states. A primitive event is a change of primitive state values and a composite event is a combination of states and/or events.

Shet et al. [168] stated that if an activity can be described in plain English, it can usually be encoded as a logical rule. The facts corresponding to primitive events are generated by background subtraction and background labeling, and the system defines composite events in a list of manners, such as theft, possess, or belong, by combining the primitive events with spatial and temporal relationships.

Ivanov and Bobick in [169] described a system for the detection and recognition of temporally

extended activities and interactions between multiple agents. The proposed system consists of an adaptive tracker, an event generator, and an activity parser. Stochastic context-free grammars (SCFGs) are used to describe activities. Low-level primitive events are detected using an HMM, and whenever a primitive event occurs, the system attempts to explain this event in the context of others by maintaining several concurrent hypotheses until one of them is confirmed with a higher probability than the others. The system is tested as part of a surveillance system in a parking lot. It correctly identifies activities such as pick-up and drop-off, which involve person-vehicle interactions.

Joo and Chellappa presented a method for representing and recognizing visual events using attribute grammars [170]. Multiple attributes are associated with primitive events. In contrast to purely syntactic grammars, attribute grammars are capable of describing features that are not easily represented by symbols. Zhang et al. [171] presented an extended grammar for learning and recognizing complex visual events. In their approach, motion trajectories of a single moving object are represented by a set of basic motion patterns, or primitives in a grammar system. A Minimum Description Length-based rule induction algorithm discovers the hidden temporal structures in the primitive stream. Finally, a multithread parsing algorithm is used to identify the interesting complex events in the primitive stream.

Ryoo and Aggarwal in [172] classified human activities into atomic action, composite action and interaction. HMMs and Bayesian networks are used to represent the atomic actions and Context-Free Grammars (CFGs) are used to model composite events and interactions. The system successfully represents and recognizes interactions such as approach, depart, point, shake-hands, hug, punch, kick, and push.

Piezuch et al. in [173] used finite state automata (FSA) to detect composite events. Regular expressions which describe composite events may easily be factorized into sub-expressions of independent expressions on the distributed cameras in the network. Similarly, Cupillard et al. [174] defined different FSAs for different types of human behaviors under different configurations. The proposed system recognizes isolated individuals, groups of people and crowd behaviors in metro scenes.

The system introduced by Black et al. [175] supports various structured query language activity queries such as object return, which returns to the field of view of a camera after an absence. Surveillance data is stored using four layers of abstraction: image frame layer, object motion

layer, semantic description layer and meta-data layer. This four-layer hierarchy supports the requirements for real-time capture and storage of detected moving objects at the lowest level and online query and activity analysis at the highest level. Similarly, Bry et al. [176] presented a method for querying composite events. A datalog-like rule language is defined to express event queries. The evaluation of the queries is reduced to the incremented evaluation of relational algebra expressions.

The event definitions above are all pre-defined. This strategy of hard-coded definition is not flexible enough to specify customized events with varying levels of complexity. To address this problem, Velipasalar et al. [177] introduced an event detection system which allows users to specify multiple composite events of high-complexity and detect their occurrence automatically. The system consists of six primitive events, such as motion, abandoned object, etc., and has five types of operator: “and”, “or”, “sequence”, “repeat-until”, and “while-do”, permitting the user to specify the parameters of primitive events and define composite events using the primitive events with the operators in the program interface.

C. Statistics-based Global Activity Understanding

Statistics-based global activity understanding methods show their power in modeling the activities surveyed by sparse camera networks. Of these methods, HMM is one of the most popular. HMM is a state-based learning architecture. States are modeled by points in a state space, and temporal transitions are modeled as sequences of random jumps from one state to another. Oliver et al. [178] compared the HMM and the coupled HMM (CHMM) for the representation of human activities. They argued that due to its coupling property, CHMM provide better representation. Hongeng and Nevatia [179] utilized the a priori duration of the event states and combined the original HMM with FSA to better approximate visual events. Their models are known as semi-HMMs.

Bayesian Belief Networks (BNs) are more general probabilistic models than HMMs. BNs are Directed Acyclic Graphs (DAGs), in which each node represents an uncertain quantity. Buxton and Gong [180] used BNs to model dynamic dependencies between parameters and to capture the dependencies between scene layout and low level image measurements for a traffic surveillance application. Loccoz et al. [181] utilized Dynamic Bayesian Networks to recognize human behaviors from video streams taken in metro stations, and established a system to recognize

violent behaviors. Labeled data are used to train the Dynamic Bayesian Networks. Similarly, Xiang and Gong [182] presented a video behavior profiling framework for anomaly detection. This framework consists of four components: 1) a behavior representation method based on discrete-scene event detection using a dynamic Bayesian network, 2) behavior pattern grouping through spectral clustering, 3) a composite generative behavior model which accommodates variations in unseen normal behavior patterns, and 4) a runtime accumulative anomaly measure to ensure robust and reliable anomaly behavior detection. This framework can be applied to many types of scenario, e.g., scenarios with crowded backgrounds. Wang et al. [183] also proposed an unsupervised learning framework to model activities and interactions in crowded and complicated scenes. In this framework, hierarchical Bayesian models are used to connect three elements: low-level visual features, simple "atomic" activities, and interactions. Atomic activities are modeled as distributions over low-level visual features, and interactions are modeled as distributions over atomic activities. These models are learned in an unsupervised way. Given a long video sequence, moving pixels are clustered into different atomic activities and short video clips are clustered into different interactions. Ryoo and Aggarwal [184] presented a probabilistic representation of group activity by describing how the individual activities of group members are organized temporally, spatially, and logically. A hierarchical recognition algorithm utilizing Markov chain Monte Carlo-based probability distribution sampling was designed to detect group activities and simultaneously find the groups.

The Petri-Net [185] is an abstract model of state-transition flow information. Petri-Nets are used in [186] to describe activities. Primitive events are represented by conditional transitions, and composite events or scenarios are represented by hierarchical transitions whose structures are derived from the event structures. Wang et al. [151] carried out activity analysis in multiple synchronized but uncalibrated static camera views using topic models. They modeled trajectories captured by different camera views into several topics, in which each topic indicated an activity path.

Hakeem and Shah [187] extended the multi-agent based event modeling method. To learn the event structure from training videos in their approach, the sub-event dependency graph is first encoded automatically and is the learned event model that depicts the conditional dependency between sub-events. The event detection is modeled by clustering the maximally correlated sub-events problem using normalized cuts. The event can thus be detected by finding the most highly

correlated chain of sub-events that have high weights (association) within the cluster and low weights (disassociation) between the clusters.

VI. FUTURE DEVELOPMENT

Although a large amount of work in sparse camera network-based visual surveillance has been undertaken, there are still many open issues worthy of further research. We briefly discuss these issues in this section.

A. Large Area Calibration

Extracting relationships between cameras is a fundamental problem in multi-camera surveillance. As discussed in Section 4, there is much work that addresses calibration over camera views, but most of this work assumes the existence of overlapping FOVs, and requires that the cameras observe a calibration object. In a large area surveillance system, however, the assumption of overlapping FOVs does not always apply. Some researchers deal with this situation by inferring the spatial-temporal topology, but topology cannot entirely take the place of calibration. When applying tracking over cameras, it is preferable to know the position of each target in a world coordinate, and topology is not enough to achieve this. To overcome the problems associated with non-overlapping FOVs, several methods are proposed, e.g., in [194], Kumar et al. relied on mirrors to make a single calibration object visible to all cameras, although their method only works well when the distances between cameras are not very large. Pflugfelder et al. [188] relied on trajectory reconstruction, but their smooth trajectories assumption was usually not applicable to large area surveillance systems. Perhaps the most promising practical method for large area calibration is through the use of auxiliary non-visual cues, such as infrared ray or GPS, to help obtain the connection between cameras or their location.

B. Green Computing Technology for Sparse Camera Network-Based Visual Surveillance

It is a great waste of energy to turn on all the cameras in a network when moving objects appear only in a small number of FOVs. In an ideal system, only the necessary cameras would be activated at any one time. This strategy reduces energy consumption and minimizes the bandwidth required by the network. When there is only one target in the surveillance area, the system should track it and predict its likely position if it enters an area outside the FOV of all the cameras.

C. Integration with Other Modalities

Human intelligence relies on several modalities; for instance, human beings may fail to distinguish surprise from fear using only visual cues, but they can successfully complete this task by listening to the subject's speech. In contrast with features based on vision alone, multi-modalities can provide more information. Similar multimodal instances can be found in machine intelligence systems, and indeed additional modalities improve the performance of vision-based surveillance systems, e.g., joint acoustic video tracking [189] and joint infrared video tracking [190]. The combination of modalities in surveillance is a significant research direction. Finding an appropriate combination is difficult, largely due to the complex relationships caused by the vast number of multimodal features and the curse of dimensionality.

D. Pan-Tilt-Zoom Camera Network

Pan-tilt-zoom (PTZ) camera networks can cover large areas and capture high-resolution information about regions of interest in dynamic scenes. In practice, systems may comprise both PTZ cameras and static wider angle cameras. The static cameras provide the positional information of targets to the PTZ cameras. Researchers have designed algorithms for collaboratively controlling a limited number of PTZ cameras to capture a number of observed targets in an optimal fashion. Optimality is achieved by maximizing the probability of successfully capturing the targets.

VII. CONCLUSION

Sparse camera network-based visual surveillance is an active and important research area, driven by applications such as smart home, security maintenance, traffic surveillance, anomalous event detection, and automatic target activity analysis.

We have reviewed the techniques used by sparse camera network-based visual surveillance systems. We have discussed the state-of-the-art methods relevant to the following issues: intra-camera tracking, inter-camera tracking, camera relationships, and global activity understanding. For intra-camera tracking, we have discussed environment modeling, motion segmentation and target tracking. For inter-camera tracking correspondence, we have discussed low-level features for visual appearance description, alignment and organization of low-level features, and inter-camera target identification. For camera relationship recovery without overlapping FOVs, we have discussed two classes of methods: camera relationship recovery based on supervised target

correspondence and camera relationship recovery based on unsupervised target correspondence. With the aid of the inter-camera relationship, global activity understanding can be carried out, by combining the information from different local cameras with spatial and temporal constraints. We have reviewed three classes of methods for activity understanding: specific activity understanding, rule-based activity understanding, and statistics-based activity understanding. We have discussed the open issues related to sparse camera network-based visual surveillance systems, including large area calibration, green computing technology, integration of other modalities and PTZ camera tracking.

REFERENCES

- [1] S. N. Sinha, M. Pollefeys, and L. McMillan, “Camera network calibration from dynamic silhouettes,” pp. 195–202, 2004.
- [2] S. N. Sinha and M. Pollefeys, “Multi-view reconstruction using photo-consistency and exact silhouette constraints: A maximum-flow formulation,” *Proc. International Conference on Computer Vision*, pp. 349–356, 2005.
- [3] R. Szeliski, “Rapid octree construction from image sequences,” *CVGIP: Image Understanding*, vol. 58, no. 1, pp. 349–356, 1993.
- [4] J. Starck and A. Hilton, “Surface capture for performance-based animation,” *IEEE Computer Graphics and Applications*, vol. 27, no. 3, pp. 21–31, 2007.
- [5] P. R. S. Medonca, K.-Y. K. Wong, and R. Cipolla, “Epipolar geometry from profiles under circular motion,” *IEEE Transactions Pattern Analysis Machine Intelligence*, vol. 23, no. 6, pp. 604–616, 2001.
- [6] C. Stauffer and K. Tieu, “Automated multi-camera planar tracking correspondence modeling,” *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. I-259–I-266, 2001.
- [7] D. C. Brown, “Close-range camera calibration,” *Photogrammetric Engineering*, vol. 37, no. 8, pp. 855–866, 1971.
- [8] G. Champleoux, S. Lavallee, P. Sautot, and P. Cinquin, “Accurate calibration of cameras and range imaging sensor: The npbs method,” *Proc. IEEE International Conference on Robotics and Automation*, pp. 1552–1557, 1992.
- [9] Q. Cai and J. K. Aggarwal, “Tracking human motion in structured environments using a distributed-camera system,” *IEEE Transactions Pattern Analysis Machine Intelligence*, vol. 2, no. 11, pp. 1241–1247, 1999.
- [10] R. T. Collins, A. J. Lipton, H. Fujiyoshi, and T. Kanade, “Algorithms for cooperative multisensory surveillance,” *Proceedings of IEEE*, vol. 89, no. 10, pp. 1456–1477, 2001.
- [11] R. Farrell, D. Doermann, and L. S. Davis, “Learning higher-order transition models in medium-scale camera networks,” *Proc. International Conference Computer Vision*, pp. 1–8, 2007.
- [12] C. Picus, R. Pflugfelder, and B. Micusik, “Branch and bound global optima search for tracking a single object in a network of non-overlapping cameras,” *Proc. International Conference Computer Vision Workshop*, pp. 1825–1830, 2011.
- [13] Y. A. Sheikh and M. Shah, “Trajectory association across multiple airborne cameras,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 2, pp. 361–367, 2008.
- [14] C. H. Kuo and C. Huang, “Inter-camera association of multi-target tracks by on-line learned appearance affinity models,” *Proc. ECCV*, pp. 383–396, 2010.
- [15] D. Makris, T. Elis, and J. Black, “Bridging the gaps between cameras,” *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. II-205–II-210, 2004.

- [16] O. Javed, Z. Rasheed, K. Shafique, and M. Shah, "Tracking across multiple cameras with disjoint views," *Proc. International Conference on Computer Vision*, pp. 952–957, 2003.
- [17] O. Williams, A. Blake, and R. Cipolla, "Sparse bayesian learning for efficient visual tracking," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 8, pp. 1292–1304, 2005.
- [18] J. Pan and B. Hu, "Robust occlusion handling in object tracking," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2007.
- [19] T. Yang, Q. Pan, J. Li, and S. Z. Li, "Real-time multiple objects tracking with occlusion handling in dynamic scenes," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 970–975, 2005.
- [20] N. Friedman and S. Russell, "Image segmentation in video sequences: A probabilistic approach," *Proc. Conference Uncertainty in Artificial Intelligence*, pp. 175–181, 1997.
- [21] D. Koller, T. Webar, J. and Huang, J. Malik, G. Ogasawara, and B. Russel, "Toward robust automatic traffic scene analysis in real-time," *Proc. International Conference on Pattern Recognition*, pp. 126–131, 1994.
- [22] M. Köhle, D. Merkl, and J. Kastner, "Clinical gait analysis by neural networks: Issues and experiences," *Proc. IEEE Symposium on Computer-Based Medical Systems*, pp. 138–143, 1997.
- [23] C. Stauffer and W. Grimson, "Adaptive background mixture models for real-time tracking," *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 246–252, 1999.
- [24] W. E. L. Grimson, C. Stauffer, R. Romano, and L. Le, "Adaptive tracking to classify and monitor activities in a site," *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 22–31, 1998.
- [25] D.-S. Lee, "Effective gaussian mixture learning for video background subtraction," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 5, pp. 827–832, 2005.
- [26] T. B. Moeslund, A. Hilton, and V. Krüger, "A survey of advances in vision-based human motion capture and analysis," *Computer Vision and Image Understanding*, vol. 104, no. 2-3, pp. 90–126, 2006.
- [27] Y. Sheikh and M. Shah, "Bayesian modeling of dynamic scenes for object detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 11, pp. 1778–1792, 2005.
- [28] A. Monnet, A. Mittal, N. Paragios, and V. Ramesh, "Background modeling and subtraction of dynamic scenes," *Proc. International Conference on Computer Vision*, pp. 1305–1312, 2003.
- [29] Y. Dong and G. N. Desouza, "Adaptive learning of multi-subspace for foreground detection under illumination changes," *Computer Vision and Image Understanding*, vol. 115, no. 1, pp. 31–49, 2011.
- [30] L. Cheng, M. Gong, D. Schuurmans, and T. Caelli, "Real-time discriminative background subtraction," *IEEE Trans. Image Processing*, vol. 20, no. 5, pp. 1401–1414, 2011.
- [31] J. Zhong and S. Sclaroff, "Segmenting foreground objects from a dynamic textured background via robust kalman filter," *Proc. International Conference on Computer Vision*, pp. 44–50, 2003.
- [32] M. Heikkila and M. Pietikainen, "A texture-based method for modeling the background and detecting moving objects," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 4, pp. 657–662, 2006.
- [33] S. McKenna, S. Jabri, Z. Duric, A. Rosenfeld, and H. Wechsler, "Tracking groups of people," *Computer Vision and Image Understanding*, vol. 80, no. 1, pp. 42–56, 2000.
- [34] M. Seki, T. Wada, H. Fujiwara, and K. Sumi, "Background subtraction based on co-occurrence of image variations," *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 65–72, 2003.
- [35] J. Yao and J.-M. Odobez, "Multi-layer background subtraction based on color and texture," *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2007.

- [36] J. Reynolds and K. Murphy, "Figure-ground segmentation using a hierarchical conditional random field," *Proc. of Canadian Conference on Computer Robot Vision*, pp. 175–182, 2007.
- [37] P.-M. Jodoin, M. Mignotte, and J. Konrad, "Statistical background subtraction using spatial cues," *IEEE Trans. Circuits and Systems for Video Technology*, vol. 17, no. 12, pp. 1758–1763, 2007.
- [38] V. Mahadevan and N. Vasconcelos, "Background subtraction in highly dynamic scenes," *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 1–6, 2008.
- [39] V. Ferrari, T. Tuytelaars, and L. van Gool, "Simultaneous object recognition and segmentation by image exploration," *Proc. European Conference on Computer Vision*, pp. 145–169, 2004.
- [40] A. B. V. K. C. Criminisi, G. Cross, "Bilayer segmentation of live video," *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 53–60, 2006.
- [41] S.-S. Huang, L.-C. Fu, and P.-Y. Hsiao, "Region-level motion-based background modeling and subtraction using mrf," *IEEE Transactions on Image Processing*, vol. 16, no. 5, pp. 1446–1456, 2008.
- [42] H. Lin, T. Liu, and J. Chuang, "Learning a scene background model via classification," *IEEE Transactions on Signal Processing*, vol. 57, no. 5, pp. 1641–1654, 2008.
- [43] M. Dikmen and T. Huang, "Robust estimation of foreground in surveillance videos by sparse error estimation," *Proc. International Conference on Pattern Recognition*, pp. 1–4, 2008.
- [44] S. Cohen, "Background estimation as a labeling problem," *Proc. International Conference Computer Vision*, pp. 1034–1041, 2005.
- [45] I. Haritaoglu, D. Harwood, and L. Davis, "W⁴: Real-time surveillance of people and their activities," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 7, pp. 809–830, 2000.
- [46] O. Barnich and M. V. Droogenbroeck, "Vibe: A universal background subtraction algorithm," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 6, pp. 1709–1724, 2011.
- [47] D. Meyer, J. Denzler, and H. Niemann, "Model based extraction of articulated objects in image sequences for gait analysis," *Proc. International Conference on Image Processing*, pp. 78–81, 1998.
- [48] L. Wang, W. Hu, and T. Tan, "Recent development in human motion analysis," *Pattern Recognition*, vol. 36, no. 3, pp. 585–601, 2003.
- [49] W. Hu, T. Tan, L. Wang, and S. Maybank, "A survey on visual surveillance of object motion and behaviors," *IEEE Transactions on Systems, Man, and Cybernetics, Part C*, vol. 34, no. 3, pp. 334–352, 2004.
- [50] A. Yilmaz, O. Javed, and M. Shah, "Object tracking: A survey," *ACM Computing Surveys*, vol. 38, no. 4, pp. 13:1–45, 2005.
- [51] A. Mittal and N. Paragios, "Motion-based background subtraction using adaptive kernel density estimation," *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. II–302–II–309, 2004.
- [52] D. J. Fleet and W. Y., "Optical flow estimation," *Handbook of Mathematical Models in Computer Vision*, Paragios et al. (eds.), 2006.
- [53] J. K. Aggarwal, *Motion Analysis: Past, Present and Future, Distributed Video Sensor Networks*. Springer, 2011.
- [54] B. Horn and B. Schunk, "Determining optical flow," *Artificial Intelligence*, vol. 17, pp. 185–203, 1981.
- [55] B. D. Lucas and T. Kanade, "An iterative image registration technique with an application to stereo vision," *Proc. International Joint Conference on Artificial Intelligence*, pp. 674–679, 1981.
- [56] M. Black and P. Anandan, "The robust estimation of multiple motions: Parametric and piecewise-smooth flow fields," *Computer Vision and Image Understanding*, vol. 63, no. 1, pp. 63–84, 1998.

- [57] N. Paperberg, A. Bruhn, T. Brox, S. Didas, and J. Wickert, "Highly accurate optic flow computation with theoretically justified warping," *International Journal of Computer Vision*, vol. 67, no. 2, pp. 141–158, 2006.
- [58] C. Lei and Y.-H. Yang, "Optical flow estimation on coarse-to-fine region-trees using discrete optimization," *Proc. International Conference on Computer Vision*, pp. 1562–1569, 2009.
- [59] B. Glocker, N. Paragios, N. Komodakis, G. Tziritas, and N. Navab, "Optical flow estimation with uncertainties through dynamic mrfs," *Proc. International Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2008.
- [60] T. Brox and J. Malik, "Large displacement optical flow: Descriptor matching in variational motion estimation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 33, no. 3, pp. 500–513, 2011.
- [61] S. Baker, D. Scharstein, J. P. Lewis, S. Roth, M. J. Black, and R. Szeliski, "A database and evaluation methodology for optical flow," *International Journal of Computer Vision*, vol. 92, no. 1, pp. 29–51, 2011.
- [62] J. Díaz, E. Ros, R. Agís, and J. L. Bernier, "Superpipelined high-performance optical-flow computation architecture," *Computer Vision and Image Understanding*, vol. 112, no. 3, pp. 262–273, 2008.
- [63] B. Zhan, D. N. Monekosso, P. Remagnino, S. A. Velastin, and L.-Q. Xu, "Crowd analysis: A survey," *Machine Vision and Applications*, vol. 19, no. 5-6, pp. 345–357, 2008.
- [64] B. Babenko, M.-H. Yang, and S. Belongie, "Visual tracking with online multiple instance learning," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 983–990, 2009.
- [65] R. T. Collins, Y. Liu, and M. Leordeanu, "Online selection of discriminative tracking features," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 10, pp. 1631–1643, 2005.
- [66] A. D. Jepson, D. J. Fleet, and T. F. El-Maraghi, "Robust online appearance models for visual tracking," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 10, pp. 1296–1311, 2003.
- [67] M. Isard and J. MacCormick, "Bramble: A bayesian multiple-blob tracker," *Proc. International Conference Computer Vision*, pp. 34–41, 2001.
- [68] B. Stenger, A. Thayananthan, P. H. S. Torr, and R. Cipolla, "Model-based hand tracking using a hierarchical bayesian filter," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 9, pp. 1372–1384, 2006.
- [69] I. A. Karaulova, P. M. Hall, and A. D. Marshall, "A hierarchical model of dynamics for tracking people with a single video camera," *Proc. British Machine Vision Conference*, pp. 352–361, 2000.
- [70] T. Zhao and R. Nevatia, "Tracking multiple humans in crowded environment," *Proc. IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 406–413, 2004.
- [71] Z. Khan, T. Balch, and F. Dellaert, "An mcmc-based particle filter for tracking multiple interacting targets," *Proc. European Conference on Computer Vision*, pp. 279–290, 2004.
- [72] J. Vermaak, A. Doucet, and P. P., "Maintaining multimodality through mixture tracking," *Proc. International Conference on Computer Vision*, pp. 1110–1117, 2003.
- [73] X. Mei and H. Ling, "Robust visual tracking using l_1 minimization," *Proc. International Conference on Computer Vision*, pp. 1436–1443, 2009.
- [74] X. Mei and H. Ling, "Robust visual tracking and vehicle classification via sparse representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 11, pp. 2259–2272, 2011.
- [75] X. Mei, H. Ling, Y. Wu, and E. Blasch, "Minimum error bounded efficient l_1 tracker with occlusion detection," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2011.
- [76] H. Li, C. Shen, and Q. Shi, "Real-time visual tracking using compressive sensing," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1305–1312, 2011.

- [77] B. Liu, L. Yang, J. Huang, P. Meer, L. Gong, and C. Kulikowski, “Robust and fast collaborative tracking with two stage sparse optimization,” *Proc. European Conference on Computer Vision*, pp. 624–637, 2010.
- [78] T. B. Dinh, N. Vo, and G. Medioni, “Context tracker: Exploring supporters and distracters in unconstrained environments,” *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1177–1184, 2011.
- [79] J. Kwon and K. M. Lee, “Tracking by sampling trackers,” *Proc. International Conference on Computer Vision*, pp. 1195–1202, 2011.
- [80] M. Li, W. Chen, K. Huang, and T. Tan, “Visual tracking via incremental self-tuning particle filtering on the affine group,” *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1315–1322, 2010.
- [81] D. S. Bolme, J. R. Beveridge, B. A. Draper, and Y. M. Lui, “Visual object tracking using adaptive correlation filters,” *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2544–2550, 2010.
- [82] D. A. Ross, J. Lim, R.-S. Lin, and M.-H. Yang, “Incremental learning for robust visual tracking,” *International Journal of Computer Vision*, vol. 77, no. 1-3, pp. 125–141, 2008.
- [83] M. Andriluka, S. Roth, and B. Schiele, “People-tracking-by detection and people-detection-by tracking,” *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2008.
- [84] C. H. Kuo, C. Huang, and R. Nevatia, “Multi-target tracking by on-line learned discriminative appearance models,” *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 685–692, 2010.
- [85] C. Huang, B. Wu, and R. Nevatia, “Robust object tracking by hierarchical association of detection responses,” *Proc. European Conference on Computer Vision*, pp. 788–801, 2008.
- [86] J. Santner, C. Leistner, A. Saffari, T. Pock, and H. Bischof, “Prost: Parallel robust online simple tracking,” *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 723–730, 2010.
- [87] T. Huang and S. Russell, “Object identification in a bayesian context,” *Proc. International Joint Conference on Artificial Intelligence*, pp. 1276–1282, 1997.
- [88] C. Nakajima, M. Pontil, B. Heisele, and T. Poggio, “Full-body person recognition system. pattern recognition,” *Pattern Recognition*, vol. 36, no. 9, pp. 1997–2006, 2003.
- [89] I. Laptev, “Improving object detection with boosted histograms,” *Image and Vision Computing*, vol. 27, no. 5, pp. 535–544, 2009.
- [90] J. Sivic, C. L. Zitnick, and R. Szeliski, “Finding people in repeated shots of the same scene,” *Proc. British Machine Vision Conference*, vol. III, pp. 909–918, 2006.
- [91] H.-U. Chae and K.-H. Jo, “Appearance feature based human correspondence under non-overlapping views,” *Proc. Fifth International Conference on Emerging Intelligent Computing Technology and Applications*, pp. 635–644, 2009.
- [92] T. Gandhi and M. M. Trivedi, “Person tracking and reidentification: Introducing panoramic appearance map (pam) for feature representation,” *Machine Vision and Application*, vol. 18, no. 3, pp. 207–220, 2007.
- [93] D. N. T. Cong, L. Khoudour, C. Achard, C. Meurie, and O. Lezoray, “People re-identification by spectral classification of silhouettes,” *Signal Processing*, vol. 90, no. 8, pp. 2362–2374, 2009.
- [94] V. Kettner and R. Zabih, “Bayesian multi-camera surveillance,” *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 253–259, 1999.
- [95] O. Oreifej, R. Mehran, and M. Shah, “Human identity recognition in aerial images,” *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 709–716, 2010.
- [96] K. Morioka, X. Mao, and H. Hashimoto, “Global color model based object matching in the multi-camera environment,” *Proc. International Conference on Intelligent Robots and Systems*, pp. 2644–2649, 2006.

- [97] F. Porikli, "Inter-camera color calibration by correlation model function," *Proc. International Conference on Image Processing*, pp. 133–136, 2003.
- [98] Z. Lin and L. Davis, "Learning pairwise dissimilarity profiles for appearance recognition in visual surveillance," *Proc. International Symposium on Advances in Visual Computing*, pp. 23–34, 2008.
- [99] S. Mitra and M. Savvides, "Gaussian mixture models based on the frequency spectra for human identification and illumination classification," *Proc. Fourth IEEE Workshop on Automatic Identification Advanced Technologies*, pp. 245–250, 2005.
- [100] R. Gross, J. Yang, and A. Waibel, "Growing gaussian mixture models for pose invariant face recognition," *Proc. International Conference on Pattern Recognition*, pp. 5088–5091, 2000.
- [101] S. McKenna and S. Gong, "Modeling facial color and identity with gaussian mixtures," *Pattern Recognition*, vol. 32, no. 12, pp. 1883–1892, 1998.
- [102] T. Tuytelaars and K. Mikolajczyk, "Local invariant feature detectors: a survey," *Computer Graphics and Vision*, vol. 3, no. 3, pp. 177–280, 2007.
- [103] K. Mikolajczyk and C. Schmid, "Scale and affine invariant interest point detectors," *International Journal of Computer Vision*, vol. 60, no. 1, pp. 63–86, 2004.
- [104] C. Harris and M. Stephens, "A combined corner and edge detector," *Proc. the Alvey Vision Conference*, pp. 147–151, 1988.
- [105] D. G. Lowe, "Object recognition from local scale-invariant features," *Proc. International Conference on Computer Vision*, pp. 1150–1155, 1999.
- [106] P. Dollár, V. Rabaud, G. Cottrell, and S. Belongie, "Behavior recognition via sparse spatio-temporal features," *Proc. International Workshop on Visual Surveillance and Performance Evaluation of Tracking and Surveillance*, pp. 65–72, 2005.
- [107] I. Laptev and T. Lindeberg, "Space-time interest points," *Proc. International Conference on Computer Vision*, pp. 432–439, 2003.
- [108] K. Mikolajczyk and C. Schmid, "A performance evaluation of local descriptors," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 10, pp. 1615–1630, 2005.
- [109] H. Bay, A. Ess, T. Tuytelaars, and L. V. Gool, "Surf: Speeded up robust features," *Computer Vision and Image Understanding*, vol. 110, no. 3, pp. 346–359, 2008.
- [110] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 886–893, 2005.
- [111] S. Belongie, J. Malik, and J. Puzicha, "Shape matching and object recognition using shape-contexts," *IEEE Transaction Pattern Analysis and Machine Intelligence*, vol. 24, no. 4, pp. 509–522, 2002.
- [112] W. S. Zheng, S. Gong, and T. Xiang, "Associating groups of people," *Proc. British Machine Vision Conference*, 2009.
- [113] X. Wang, G. Doretto, T. Sebasitan, J. Rittscher, and P. Tu, "Shape and appearance context modeling," *Proc. International Conference Computer Vision*, pp. 1–8, 2007.
- [114] O. Hamdoun, F. Moutarde, B. Stanciulescu, and B. Steux, "Person re-identification in multi-camera system by signature based on interest point descriptors collected on short video sequences," *Proc. 2nd ACM/IEEE International Conference on Distributed Smart Cameras*, pp. 1–6, 2008.
- [115] I. Laptev and T. Lindeberg, "Local descriptors for spatio-temporal recognition," *Proc. ECCVW*, pp. 91–103, 2004.
- [116] D. Gabor, *Theory of Communication*. IEEE, 1946.

- [117] D. Gray and H. Tao, "Viewpoint invariant pedestrian recognition with an ensemble of localized features," *Proc. European Conference on Computer Vision*, pp. 262–275, 2008.
- [118] C. Schmid, "Constructing models for content-based image retrieval," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 39–45, 2001.
- [119] I. Fogel and D. Sagi, "Gabor filters as texture discriminator," *Formal Aspects of Computing*, vol. 61, no. 2, pp. 103–113, 1989.
- [120] L. Bazzani, M. Cristani, A. Perina, M. Farenzena, and V. Murino, "Multiple-shot person re-identification by hpe signature," *Proc. International Conference on Pattern Recognition*, pp. 1413–1416, 2010.
- [121] M. Farenzena, L. Bazzani, A. Perina, V. Murino, and M. Cristani, "Person re-identification by symmetry-driven accumulation of local features," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2360–2367, 2010.
- [122] P. E. Forssén, "Maximally stable colour regions for recognition and matching," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2007.
- [123] N. D. Bird, O. Masoud, N. P. Papanikopoulos, and A. Isaacs, "Detecting of loitering individuals in public transportation areas," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 2, pp. 167–177, 2005.
- [124] S. Si, D. Tao, and B. Geng, "Bregman divergence-based regularization for transfer subspace learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 7, pp. 929–942, 2010.
- [125] L. T. Song, Y., "Context-aided human recognition-clustering," *Proc. European Conference on Computer Vision*, pp. 382–395, 2006.
- [126] D. Tao, X. Li, X. Wu, and S. J. Maybank, "General tensor discriminant analysis and gabor features for gait recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 10, pp. 1700–1715, 2007.
- [127] J. M. Seigneur, D. Solis, and F. Shevlin, "Ambient intelligence through image retrieval," *Proc. Image and video retrieval*, pp. 526–534, 2004.
- [128] M. Sonka, V. Hlavac, and R. Boyle, *Image processing, analysis, and machine vision*, 2nd edn. MA: PWS Publishing, 1999.
- [129] L. Wang, T. Tan, H. Ning, and W. Hu, "Silhouette analysis-based gait recognition for human identification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 12, pp. 1505–1518, 2003.
- [130] N. Gheissari, T. B. Sebastian, P. H. Tu, and J. Rittscher, "Person reidentification using spatiotemporal appearance," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1528–1535, 2006.
- [131] L. P. S. Brin, "The anatomy of a large-scale hypertextual web search engine," *Proc. World Wide Web*, 1998.
- [132] L. J. G. Y. Rubner, C. Tomasi, "The earth mover's distance as a metric for image retrieval," *International Journal of Computer Vision*, vol. 40, no. 2, pp. 99–121, 2000.
- [133] W. R. Schwartz and L. S. Davis, "Learning discriminative appearance-based models using partial least squares," *Proc. Brazilian Symposium on Computer Graphics and Image Processing*, pp. 322–329, 2009.
- [134] P. Felzenszwalb, R. B. Girshick, and D. McAllester, "Cascade object detection with deformable part models," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2241–2248, 2010.
- [135] S. Agarwal, A. Awan, and D. Roth, "Learning to detect objects in images via a sparse, part-based representation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 26, no. 11, pp. 1475–1490, 2004.
- [136] P. Felzenszwalb, D. McAllester, and D. Ramaman, "A discriminatively trained, multiscale, deformable part model," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2008.

- [137] P. Dollár, B. Babenko, S. Belongie, P. Perona, and Z. Tu, "Multiple component learning for object detection," *Proc. European Conference on Computer Vision*, pp. 211–224, 2008.
- [138] S. Kwak, W. Nam, and B. Han, "Learning occlusion with likelihoods for visual tracking," *Proc. International Conference on Computer Vision*, pp. 1551–1558, 2011.
- [139] P. Felzenszwalb, R. Girshick, D. McAllester, and D. Ramanan, "Object detection with discriminatively trained part-based models," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 9, pp. 1627–1645, 2010.
- [140] S. Andrews, I. Tsachantaridis, and T. Hofmann, "Support vector machines for multiple-instance learning," *Proc. Neuroal Information Processing System*, pp. 561–568, 2003.
- [141] O. Javed, K. Shafique, Z. Rasheed, and M. Shah, "Modeling inter-camera space-time and appearance relationships for tracking across non-overlapping views," *Computer Vision and Image Understanding*, vol. 109, no. 2, pp. 146–162, 2008.
- [142] K. W. Chen, C. Lai, Y. P. Hung, and C. Chen, "An adaptive learning method for target tracking across multiple cameras," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2008.
- [143] X. Zou, B. Bhanu, B. Song, and A. K. R. Chowdhury, "Determining topology in distributed camera network," *Proc. International Conference, on Image Processing*, pp. 133–136, 2007.
- [144] C. Niu and E. Grimson, "Recovering non-overlapping network topology using far-field vehicle tracking data," *Proc. International Conference on Pattern Recognition*, pp. 944–949, 2006.
- [145] O. Javed, K. Shafique, and M. Shah, "Appearance modeling of tracking in multiple non-overlapping cameras," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 26–33, 2007.
- [146] C. Stauffer, "Learning to track objects through unobserved regions," *Proc. IEEE Workshop on Motion and Video Computing*, pp. 96–102, 2005.
- [147] A. Gilbert and R. Bowden, "Tracking objects across cameras by incrementally learning inter-camera colour calibration and patterns of activity," *Proc. European Conference on Computer Vision*, pp. 125–136, 2006.
- [148] K. Tieu, G. Dalley, and W. Grimson, "Inference of non-overlapping camera network topology by measuring statistical dependence," *Proc. International Conference on Computer Vision*, pp. 1842–1849, 2005.
- [149] D. Marinakis, G. Dudek, and D. J. Fleet, "Learning sensor network topology through monte carlo expectation maximization," *Proc. International Conference on Robotics and Automation*, pp. 4581–4587, 2005.
- [150] C. C. Loy, T. Xiang, and S. Gong, "Multi-camera activity correlation analysis," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1988–1995, 2009.
- [151] X. Wang, K. Tieu, and E. L. Grimson, "Correspondence-free activity analysis and scene modeling in multiple camera views," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 1, pp. 56–71, 2010.
- [152] J. K. Aggarwal and M. S. Ryoo, "Human activity analysis: A review," *ACM Computing Surveys*, vol. 43, no. 2, pp. 16:1–43, 2011.
- [153] B. T. Morris and M. M. Trivedi, "A survey of vision-based trajectory learning and analysis for surveillance," *IEEE Transactions on Circuits and Systems*, vol. 18, no. 8, pp. 1114–1127, 2008.
- [154] D. Weinland, R. Ronfard, and E. Boyer, "A survey of vision-based methods for action representation, segmentation and recognition," *Computer Vision and Image Understanding*, vol. 115, no. 2, pp. 224–241, 2011.
- [155] E. Stringa and C. Regazzoni, "Real-time video-shot detection for scene surveillance applications," *IEEE Transactions on Image Processing*, vol. 9, no. 1, pp. 69–79, 2000.
- [156] H. Watanabe, H. Tanahashi, Y. Satoh, Y. Niwa, and K. Yamamoto, "Event detection for a visual surveillance system using

- stereo omni-directional system," *Proc. Knowledge based Intelligent Information and Engineering System*, pp. 890–896, 2003.
- [157] T. Ahmedali and J. J. Clark, "Collaborative multi-camera surveillance with automated person detection," *Proc. Canadian Conference on Computer and Robot Vision*, p. 39, 2006.
 - [158] K. Kim and L. S. Davis, "Multi-camera tracking and segmentation of occluded people on ground plane using search-guided particle filtering," *Proc. European Conference on Computer Vision*, pp. 98–109, 2006.
 - [159] A. Prest, C. Schmid, and V. Ferrari, "Weakly supervised learning of interactions between humans and objects," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 3, pp. 601–614, 2011.
 - [160] H. Wang, A. Kläser, C. Schmid, and L. Cheng-Lin, "Action recognition by dense trajectories," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3169–3176, 2011.
 - [161] J. Allen and G. Ferguson, "Actions and events in interval temporal logic," *Journal of Logic and Computation, Special Issue on Actions and Process*, vol. 4, no. 5, pp. 531–579, 1994.
 - [162] G. Foresti, L. Marcenaro, and C. S. Regazzoni, "Automatic detection and indexing of video-event shots for surveillance applications," *IEEE Transactions on Multimedia*, vol. 4, no. 4, pp. 459–471, 2002.
 - [163] R. Nevatia, T. Zhao, and S. Hongeng, "Hierarchical language-based representation of events in video streams," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 39–39, 2003.
 - [164] R. Nevatia, J. Hobbs, and B. Bolles, "An ontology for video event representation," *Proc. IEEE Conference on Computer Vision and Pattern Recognition Workshop*, pp. 119–119, 2004.
 - [165] A. R. J. Francois, R. Nevatia, J. Hobbs, R. C. Bolles, and J. R. Smith, "Verl: An ontology framework for representing and annotating video events," *IEEE Multimedia*, vol. 12, no. 4, pp. 76–86, 2005.
 - [166] A. Boukerche, D. D. Duarte, and R. Borges de Araujo, "Veml: A mark-up language to describe web-based virtual environment through atomic simulations," *Proc. IEEE International Symposium on Distributed Simulation and Real-time Applications*, pp. 214–217, 2004.
 - [167] M. Borg, D. Thirde, F. Fusier, and V. Valentin, "Video surveillance for aircraft activity monitoring," *Proc. IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 16–21, 2005.
 - [168] V. Shet, D. Harwood, and L. S. Davis, "Vidmap: Video monitoring of activity with prolog," *Proc. IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 224–229, 2005.
 - [169] Y. A. Ivanov and A. F. Bobick, "Recognition of multi-agent interaction in video surveillance," *Proc. International Conference on Computer Vision*, pp. 169–176, 1999.
 - [170] S. Joo and R. Chellappa, "Recognition of multi-object events using attribute grammars," *Proc. International Conference on Image Processing*, pp. 2897–2900, 2006.
 - [171] Z. Zhang, T. Tan, and K. Huang, "An extended grammar system for learning and recognizing complex visual events," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 2, pp. 240–255, 2011.
 - [172] M. S. Ryoo and J. K. Aggarwal, "Recognition of composite human activities through context-free grammar based representation," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1709–1718, 2006.
 - [173] P. Piezuch, B. Shand, and J. Bacon, "Composite event detection as a generic middleware extension," *IEEE Network*, vol. 18, no. 1, pp. 44–55, 2004.
 - [174] F. Cupillard, A. Avanzi, and F. Bremond, "Video understanding for metro surveillance," *Proc. IEEE Conference on Networking, Sensing & Control*, pp. 186–191, 2004.

- [175] J. Black, T. Ellis, and D. Makris, "A hierarchical database for visual surveillance applications," *Proc. International Conference on Multimedia and Expo*, pp. 1571–1574, 2004.
- [176] F. Bry and M. Eckert, "Temporal order optimizations of incremental joins for composite event detection," *Proc. International Conference on Distributed Event-based Systems*, pp. 85–90, 2007.
- [177] S. Velipasalar, L. M. Brown, and A. Hampapur, "Specifying, interpreting and detecting high-level, spatio-temporal composite events in single and multi-cameras systems," *Proc. IEEE Conference on Computer Vision and Pattern Recognition Workshop*, p. 110, 2006.
- [178] N. M. Oliver, B. Rosario, and A. P. Pentland, "A bayesian computer vision system for modeling human interactions," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 8, pp. 831–843, 2000.
- [179] S. Hongeng and R. Nevatia, "Large- scale event detection using semi-hidden markov models," *Proc. International Conference on Computer Vision*, pp. 1455–1462, 2003.
- [180] H. Buxton and S. Gong, "Visual surveillance in a dynamic and uncertain world," *Artificial Intelligence*, vol. 78, no. 1-2, pp. 431–459, 1995.
- [181] N. Loccoz, F. Brémond, and M. Thonnat, "Recurrent bayesian network for the recognition of human behaviors from video," *Proc. International Conference on Computer Vision Systems*, pp. 68–77, 2003.
- [182] T. Xiang and S. Gong, "Video behavior profiling for anomaly detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 5, pp. 893–908, 2008.
- [183] X. Wang, X. Ma, and W. E. L. Grimson, "Unsupervised activity perception in crowded and complicated scenes using hierarchical bayesian models," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 31, no. 3, pp. 539–555, 2009.
- [184] M. S. Ryoo and J. K. Aggarwal, "Stochastic representation and recognition of high-level group activities," *International Journal of Computer Vision*, vol. 93, no. 2, pp. 183–200, 2011.
- [185] C. Petri, *Communication with automata*. DTIC Research Report AD0630125, 1966.
- [186] N. Ghanem, D. DeMenthon, D. Doermann, and L. Davis, "Representation and recognition of events in surveillance video using petri nets," *Proc. Computer Vision and Pattern Recognition Workshop*, pp. 811–818, 2004.
- [187] M. S. A. Hakeem, "Learning, detection and representation of multi-agent events in videos," *Artificial Intelligence*, vol. 171.
- [188] R. Pflugfelder and H. Bischof, "Localization and trajectory reconstruction in surveillance cameras with nonoverlapping views," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 4, pp. 709–721, 2010.
- [189] V. Cevher, A. Sankaranarayanan, J. H. McClellan, and R. Chellappa, "Target tracking using a joint acoustic video system," *IEEE Transactions on Multimedia*, vol. 9, no. 4, pp. 715–727, 2007.
- [190] N. Cvejic, S. G. Nikolov, H. D. Knowles, A. T. Loza, A. M. Achim, D. R. Bull, and C. N. Canagarajah, "The effect of pixel-level fusion on object tracking in multi-sensor surveillance video," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–7, 2007.

